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LIMIT THEORY FOR THE SAMPLE COVARIANCE AND CORRELATION
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HILL CENTER FOR STOCHASTIC PREC. R DAVIS ET AL.

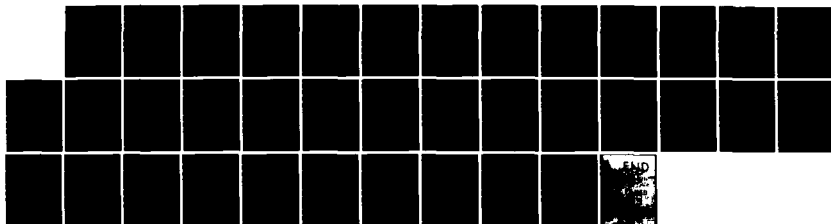
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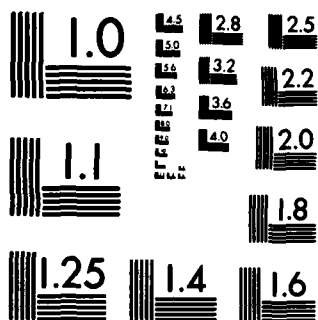
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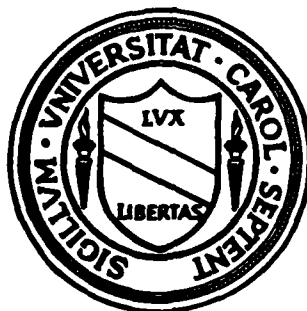


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CENTER FOR STOCHASTIC PROCESSES

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Chapel Hill, North Carolina



Limit Theory for the Sample Covariance and Correlation Functions of Moving Averages

Richard Davis
and
Sidney Resnick

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Limit Theory for the Sample Covariance and Correlation

Functions of Moving Averages

By

Richard Davis* and Sidney Resnick**

Colorado State University

Document

Abstract

describes

Let $X_t = \sum_{j=-\infty}^{\infty} c_j Z_{t-j}$ be a moving average process where the Z_t 's are iid

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Running head: Limit theory for moving averages.

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(1.3) was given by Kanter and Steiger (1974) and Hannan and Kanter (1977). They proved that for any $\delta > \alpha$,

$$n^{1/\delta} (\hat{\rho}(h) - \rho(h)) \xrightarrow{P} 0$$

with a similar result holding for the least squares estimates of the parameters in the AR(p) model. Yohai and Maronna (1977) also considered AR(p) processes and showed that $n^{1/2} (\hat{\rho}(h) - \rho(h))$ is bounded in probability provided the Z_t 's are symmetrically distributed and $E \log^+ |Z_t| < \infty$. Of course if the Z_t 's have a finite variance then $n^{1/2} (\hat{\rho}(h) - \rho(h))$ is asymptotically normal under mild restrictions on the coefficients $\{c_j\}$ (cf. Anderson, 1971, p. 489).

In Section 2, the limit distribution of the sample covariance function is derived for the case $2 \leq \alpha < 4$. In the special case, $2 < \alpha < 4$, the process has a finite variance but an infinite fourth moment. It turns out that, as in the $0 < \alpha < 2$ case, the limit behavior of the sample covariance function is determined by the partial sums $\sum_{t=1}^n Z_t^2$. We also consider in Section 2 the situation when Z_t^2 belongs to the normal domain of attraction with an infinite variance.

The weak limit of the sample correlation function in the infinite variance case ($0 < \alpha < 2$) is considered in Section 4. It is shown that there exists a slowly varying function at ∞ , $\tilde{L}(\cdot)$, such that $n^{1/\alpha} \tilde{L}(n) (\hat{\rho}(h) - \rho(h))$ converges in distribution to the ratio of two independent stable random variables with indices α and $\alpha/2$ respectively. Whereas the asymptotic properties of the sample covariance function are governed by the partial sums $\sum_{t=1}^n Z_t^2$, the weak limit behavior of the sample correlation function is determined by the vector of partial sums $(\sum_{t=1}^n Z_t^2, \sum_{t=1}^n Z_t Z_{t+1}, \dots, \sum_{t=1}^n Z_t Z_{t+h})$. In Section 3, we show that this sequence of vector-valued random variables converges in distribution to a vector of independent non-normal stable random variables. This result is proved using point process techniques and ideas from extreme value theory.

A discussion of least squares estimates for AR(p) processes in this setting

and some examples are presented in Section 5.

2. Sample covariance function

The aim of this section is to derive the weak limit of the sample covariance function for the process $\{X_t\}$ satisfying (1.1) with $2 \leq \alpha < 4$. Assume

$$(2.1) \quad X_t = \sum_{j=-\infty}^{\infty} c_j Z_{t-j} \quad \text{with} \quad \sum_{j=-\infty}^{\infty} |c_j| < \infty$$

where the Z_t satisfies (1.2) and (1.3). Put $a_n = \inf\{x: P(|Z_1| > x) \geq n^{-1}\}$ and define the sample covariance function by

$$\hat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^n X_t X_{t+h}, \quad h \geq 0.$$

The following proposition is the key step in evaluating the weak limit behavior of $\hat{\gamma}(h)$.

Proposition 2.1. If $2 \leq \alpha < 4$ and $E Z_t = 0$, then for every positive integer h ,

$$(2.2) \quad a_n^{-2} (n \hat{\gamma}(h) - \sum_{t=1}^n \sum_{i=-\infty}^{\infty} c_i c_{i+h} Z_{t-i}^2) \xrightarrow{P} 0.$$

Proof. We have

$$\begin{aligned} & a_n^{-2} \left(\sum_{t=1}^n X_t X_{t+h} - \sum_{t=1}^n \sum_{i=-\infty}^{\infty} c_i c_{i+h} Z_{t-i}^2 \right) \\ &= a_n^{-2} \left(\sum_{t=1}^n \sum_{i \neq j} c_i c_{j+h} Z_{t-i} Z_{t-j} \right) \\ &= a_n^{-2} \sum_{t=1}^n \sum_{i \neq j} c_i c_{j+h} (Z_{t-i}^2 1[|Z_{t-i}| \leq a_n] - \mu_n) (Z_{t-j}^2 1[|Z_{t-j}| \leq a_n] - \mu_n) \\ &\quad + a_n^{-2} \mu_n \sum_{t=1}^n \sum_{i \neq j} c_i c_{j+h} (Z_{t-i}^2 1[|Z_{t-i}| \leq a_n] + Z_{t-j}^2 1[|Z_{t-j}| \leq a_n]) \\ &\quad + a_n^{-2} \sum_{t=1}^n \sum_{i \neq j} c_i c_{j+h} Z_{t-i} Z_{t-j} 1[|Z_{t-i}| > a_n \text{ or } |Z_{t-j}| > a_n] \\ &\quad - n a_n^{-2} \mu_n^2 \sum_{i \neq j} c_i c_{j+h} \\ &= A + B + C + D \end{aligned}$$

where $\mu_n = E Z_1^{-1} [|Z_1| \leq a_n]$. We shall show that $A, B, C \xrightarrow{P} 0$ and $D \rightarrow 0$.

Define

$$Z_{t,n} = Z_t^{-1} [|Z_t| \leq a_n] - \mu_n$$

and we have

$$\text{Var}(A) = a_n^{-4} \sum_{s=1}^n \sum_{t=1}^n \sum_{i \neq j} \sum_{k \neq l} c_i c_{j+h} c_k c_{l+h} E(Z_{t-i,n} Z_{t-j,n} Z_{s-k,n} Z_{s-l,n}).$$

Since $\{Z_{t,n}, -\infty < t < \infty\}$ is for each n an iid sequence of zero mean random variables, the above expectation is zero unless $\{t-i, t-j\} = \{s-k, s-l\}$. When this is the case, the expectation is of the form

$$\begin{aligned} E Z_{1,n}^2 Z_{2,n}^2 &= E Z_{1,n}^2 E Z_{2,n}^2 \\ &\leq (E Z_1^{-2} [|Z_1| \leq a_n])^2 = \sigma_n^4 \end{aligned}$$

where $\sigma_n^2 = E Z_1^{-2} [|Z_1| \leq a_n]$. Hence

$$\begin{aligned} \text{Var}(A) &\leq a_n^{-4} \sigma_n^4 \sum_{s=1}^n \sum_{t=1}^n \sum_{i \neq j} (|c_i| |c_{j+h}| |c_{s-t+i}| |c_{s-t+j+h}| \\ &\quad + |c_i| |c_{j+h}| |c_{s-t+j}| |c_{s-t+i+h}|) \\ &\leq \sigma_n^4 a_n^{-4} \sum_{s=1}^n \sum_{t=1}^n ((\sum_i |c_i c_{i+s-t}|)^2 + (\sum_i |c_i c_{i+h+s-t}|)(\sum_j |c_{j+h} c_{j+s-t}|)) \\ &\leq \sigma_n^4 a_n^{-4} n \sum_{|t| < n} ((\sum_i |c_i c_{i+t}|)^2 + (\sum_i |c_i c_{i+h+t}|)(\sum_j |c_{j+h} c_{t+j}|)) \\ &\leq 2(\sum_i |c_i|)^4 n a_n^{-4} \sigma_n^4 \end{aligned}$$

For $2 < \alpha < 4$, σ_n^2 has a finite limit and in the $\alpha = 2$ case it is slowly varying by Karamata's Theorem (Feller, 1971). So in either case σ_n^4 is slowly varying. Moreover, a_n is regularly varying with index $1/\alpha$ which together with the slow variation of σ_n^4 implies $n a_n^{-4} \sigma_n^4 \rightarrow 0$ as $n \rightarrow \infty$. Thus, $\text{Var}(A) \rightarrow 0$ as desired.

As for the term B, we have

$$\begin{aligned} E|B| &\leq 2 n a_n^{-2} |\mu_n| \left(\sum_1 |c_i| \right)^2 E|Z_1| 1_{[|Z_1| \leq a_n]} \\ &\leq 2 \left(\sum_1 |c_i| \right)^2 E|Z_1| n a_n^{-2} |\mu_n|. \end{aligned}$$

Since $E Z_t = 0$ by assumption, $|\mu_n| = |E Z_1 1_{[|Z_1| > a_n]}| \leq E|Z_1| 1_{[|Z_1| > a_n]} \sim \frac{\alpha-1}{\alpha} a_n/n$

by Karamata's Theorem. Hence $n a_n^{-2} |\mu_n| \rightarrow 0$ as $n \rightarrow \infty$.

Next

$$\begin{aligned} E|C| &\leq n a_n^{-2} \left(\sum_1 |c_i| \right)^2 E|Z_1 Z_2| 1_{[|Z_1| > a_n \text{ or } |Z_2| > a_n]} \\ &\leq 2 n a_n^{-2} \left(\sum_1 |c_i| \right)^2 E|Z_2| E|Z_1| 1_{[|Z_1| > a_n]} \\ &\rightarrow 0 \end{aligned}$$

by Karamata's Theorem as for B. Finally, $D = O(n a_n^{-2} \mu_n^2) \rightarrow 0$ since for B we have already proved $n a_n^{-2} |\mu_n| \rightarrow 0$ and this completes the proof. \square

For $\alpha > 2$, define

$$\begin{aligned} \gamma(h) &= \text{Cov}(X_t, X_{t+h}) \\ &= \left(\sum_{j=-\infty}^{\infty} c_j c_{j+h} \right) \cdot \sigma^2 \end{aligned}$$

where $\sigma^2 = \text{Var}(Z_t)$. The next theorem gives the main result of this section.

Here and in what follows, convergence in distribution is denoted by " \Rightarrow ".

Theorem 2.2. Suppose $\{X_t\}$ is given by (2.1) where $\{Z_t\}$ satisfies (1.2) and (1.3) with $2 \leq \alpha < 4$. If $E Z_t = 0$, then for any positive integer ℓ

$$(2.3) \quad (n a_n^{-2} (\hat{\gamma}(h) - b_{h,n}), 0 \leq h \leq \ell) \Rightarrow S \cdot \left(\sum_j c_j^2, \sum_j c_j c_{j+1}, \dots, \sum_j c_j c_{j+\ell} \right)$$

where S is a stable random variable with index $\alpha/2$ and $b_{h,n} = \sum_{i=-\infty}^{\infty} c_i c_{i+h} E Z_1^2 1_{[|Z_1| \leq a_n]}$,

$0 \leq h \leq \ell$. Moreover, if $2 < \alpha < 4$, then

$$(2.4) \quad (n a_n^{-2} (\hat{\gamma}(h) - \gamma(h)), 0 \leq h \leq \ell) \Rightarrow (S - \frac{\alpha}{\alpha-2})(\gamma(0), \dots, \gamma(\ell))/\sigma^2.$$

Proof. By Theorem 4.1 in Davis and Resnick (1984),

$$a_n^{-2} \sum_{t=1}^n \sum_{i=-\infty}^{\infty} c_i c_{i+h} (Z_{t-1}^2 - \sigma_n^2) \Rightarrow \sum_{i=-\infty}^{\infty} c_i c_{i+h} S \text{ for all } h \geq 0$$

where $\sigma_n^2 = E Z_1^2 1[|Z_1| \leq a_n]$ and S is a stable random variable with index $\alpha/2$.

From the proof of this same theorem, we have for any positive integer l

$$a_n^{-2} \left(\sum_{t=1}^n \sum_{i=1}^n c_i^2 (Z_{t-1}^2 - \sigma_n^2), \sum_{t=1}^n \sum_{i=1}^n c_i c_{i+1} (Z_{t-1}^2 - \sigma_n^2), \dots, \sum_{t=1}^n \sum_{i=1}^n c_i c_{i+l} (Z_{t-1}^2 - \sigma_n^2) \right) \\ \Rightarrow S \left(\sum_{j=1}^n c_j^2, \sum_{j=1}^n c_j c_{j+1}, \dots, \sum_{j=1}^n c_j c_{j+l} \right).$$

This combined with Proposition 2.1 proves (2.3).

If $\alpha > 2$, then $\sigma_n^2 \rightarrow \sigma^2$ and by Karamata's Theorem, $n \sigma_n^2 a_n^{-2} - n \sigma_n^2 a_n^{-2} = n a_n^{-2} E Z_1^2 1[|Z_1| > a_n] \rightarrow \frac{\alpha}{\alpha-2}$, so that by the convergence of types result, (2.4) holds. \square

Corollary. The same limit law is attained in Theorem 2.2 if $\hat{\gamma}(h)$ is replaced by a mean corrected version

$$\tilde{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-h} (X_t - \bar{X})(X_{t+h} - \bar{X}) \text{ where } \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i.$$

The proof of this corollary is analogous to that of the corollary following Theorem 4.2 in Davis and Resnick (1984) and is therefore omitted. Also note that the corollary remains true if $E Z_t \neq 0$ by considering the process $X_t - E X_t = \sum_{j=-\infty}^{\infty} c_j (Z_{t-j} - E Z_{t-j})$.

Corresponding to the case $\alpha = 4$ we have the following result.

Proposition 2.3. Suppose $\{X_t\}$ is defined by (2.1) with $E Z_t = 0$ and

$$E Z_1^4 1[|Z_1| \leq t] = L(t)$$

is slowly varying with $\lim_{t \rightarrow \infty} L(t) = \infty$. Define α_n by

$$\frac{nL(\alpha_n^{1/2})}{\alpha_n^2} \rightarrow 1$$

so that α_n is regularly varying with index $1/2$. If $a_n = \alpha_n^{1/2}$ then in \mathbb{R}^{l+1}

$$(2.5) \quad (n a_n^{-2} (\hat{\gamma}(h) - \gamma(h)), 0 \leq h \leq l) \Rightarrow N \cdot (\gamma(0), \dots, \gamma(h))/\sigma^2$$

where N is a $N(0, 1)$ random variable.

Remarks. (1) Define $L_1(x) = L(x^{1/2})$ so that L_1 is also slowly varying (de Haan, 1970, p. 21). Then α_n must satisfy $n L_1(\alpha_n)/\alpha_n^2 \rightarrow 1$. Set $U_1(x) = x^2/L_1(x)$ so that U_1 is regularly varying with index 2 and α_n satisfies $U_1(\alpha_n) \sim n$ and this shows α_n may be taken as the asymptotic inverse of U_1 at the point n (cf. Seneta, 1976, p. 21).

(2) For the classical result assuming $E Z_1^4 < \infty$ see Anderson, 1971, p. 478.

Proof. We begin by showing the analogue of Proposition 2.1. The difference

$$a_n^{-2} (n \hat{\gamma}(h) - \sum_{t=1}^n \sum_{i=-\infty}^{\infty} (c_i c_{i+h}) Z_{t-i}^2)$$

is again decomposed into the pieces $A + B + C + D$.

We have $\text{Var}(A) = O(n a_n^{-4})$. Since $L(t) \rightarrow \infty$ we have $\alpha_n/\sqrt{n} \rightarrow \infty$ and hence

$$n a_n^{-4} = n \alpha_n^{-2} \rightarrow 0$$

as desired. For B we have

$$E |B| \leq (\text{const}) n a_n^{-2} E |Z_1| 1_{[|Z_1| > a_n]}.$$

Since $L(t) = \int_0^t z^4 P[|Z_1| \leq dz]$ we have

$$\begin{aligned} E |Z_1| 1_{[|Z_1| > a_n]} &= \int_{a_n}^{\infty} z P[|Z_1| \leq dz] = \int_{a_n}^{\infty} t^{-3} L(dt) \\ &= 3 \int_{a_n}^{\infty} L(s) s^{-4} ds - L(a_n) a_n^{-3} \\ &= a_n^{-3} L(a_n) \left\{ \int_1^{\infty} 3(L(as)/L(a_n)) s^{-4} ds - 1 \right\} \end{aligned}$$

so that

$$n a_n^{-2} E |Z_1|^{-1} 1_{[|Z_1| > a_n]} = n L(a_n) a_n^{-5} \left\{ \int_1^\infty 3(L(a_n s)/L(a_n)) s^{-4} ds - 1 \right\}.$$

However, since $n L(a_n) a_n^{-4} \rightarrow 1$, the above term is asymptotic to

$$a_n^{-1} \left\{ \int_1^\infty 3(L(a_n s)/L(a_n)) s^{-4} ds - 1 \right\}$$

which goes to zero since $a_n \rightarrow \infty$ and the expression within the braces goes to zero by Karamata's Theorem. The term $E|C|$ is handled in the same way and D is of smaller order than $E|B|$ so the analogue of Proposition 2.1 is proved. \square

Before continuing with the proof we need the following result.

Proposition 2.4. Suppose $\{X_t\}$ satisfies (2.1) with $E Z_1 = 0$ and $U(t) = E Z_1^2 1_{[|Z_1| \leq t]}$

slowly varying. Define g_n by

$$n g_n^{-2} E Z_1^2 1_{[|Z_1| \leq g_n]} \rightarrow 1.$$

Then

$$g_n^{-1} \sum_{t=1}^n X_t \Rightarrow \left(\sum_{j=-\infty}^{\infty} c_j \right) N$$

where N is $N(0, 1)$.

Proof. A proof can be fashioned after the method used in Davis and Resnick (1984)

to prove Theorem 4.1. We have Z_1 in the domain of attraction of the normal so that $g_n^{-1} \sum_{i=1}^n Z_i \Rightarrow N$. Furthermore for $m \geq 1$

$$Y_n = \left\{ g_n^{-1} \sum_{t=1}^n Z_{t-j}, |j| \leq m \right\} \Rightarrow (N, N, \dots, N)$$

in \mathbb{R}^{2m+1} and therefore by the continuous mapping theorem

$$(c_{-m}, \dots, c_m) \cdot Y_n \Rightarrow \left(\sum_{|j| \leq m} c_j \right) N.$$

It remains to show

$$(2.6) \quad \lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} P \left[\left| g_n^{-1} \sum_{t=1}^n X_t - (c_{-m}, \dots, c_m) \cdot Y_n \right| > \delta \right] = 0$$

for any $\delta > 0$ as well as

$$(2.7) \quad \left(\sum_{|j| \leq m} c_j \right) N \Rightarrow \left(\sum_{j=-\infty}^{\infty} c_j \right) N, \quad m \rightarrow \infty.$$

The validity of (2.7) is obvious.

We have that

$$\begin{aligned} g_n^{-1} \sum_{t=1}^n X_t &= (c_{-m}, \dots, c_m) \cdot X_n = g_n^{-1} \sum_{t=1}^n \sum_{|j| > m} c_j Z_{t-j} \\ &= g_n^{-1} \sum_{t=1}^n \sum_{|j| > m} c_j (Z_{t-j} 1_{[|Z_{t-j}| \leq g_n]} - E Z_1 1_{[|Z_1| \leq g_n]}) \\ &\quad + g_n^{-1} n \left(\sum_{|j| > m} c_j \right) E Z_1 1_{[|Z_1| \leq g_n]} \\ &\quad + g_n^{-1} \sum_{t=1}^n \left(\sum_{|j| > m} c_j \right) Z_{t-j} 1_{[|Z_{t-j}| > g_n]} \\ &= \alpha + \beta + \gamma. \end{aligned}$$

Now

$$\lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} P[|\alpha| > \delta] = 0$$

by an argument identical to one used in the proof of Theorem 4.1 of Davis and Resnick (1984). (We use the fact that $n g_n^{-2} E Z_1^2 1_{[|Z_1| \leq g_n]} \rightarrow 1$.) For the other two terms we calculate

$$\begin{aligned} |E Z_1 1_{[|Z_1| \leq g_n]}| &= |E Z_1 1_{[|Z_1| > g_n]}| \\ &\leq E |Z_1| 1_{[|Z_1| > g_n]} = \int_{g_n}^{\infty} t P[|Z_1| \in dt] = \int_{g_n}^{\infty} t^{-1} U(dt) \\ &= \int_{g_n}^{\infty} s^{-2} U(s) ds = g_n^{-1} U(g_n) \end{aligned}$$

and so applying Karamata's Theorem (recall U is slowly varying) we get

$$\lim_{n \rightarrow \infty} \frac{g_n E Z_1^{-1} [|Z_1| \leq g_n]}{U(g_n)} = 0.$$

Thus

$$\begin{aligned} |\beta| &\leq g_n^{-1} n \left| E Z_1^{-1} [|Z_1| \leq g_n] \right| \sum_{|j| > m} |c_j| \\ &= \frac{n U(g_n)}{g_n^2} \frac{g_n |E Z_1^{-1} [|Z_1| \leq g_n]|}{U(g_n)} \sum_{|j| > m} |c_j| \\ &\sim g_n |E Z_1^{-1} [|Z_1| \leq g_n]| \sum_{|j| > m} |c_j| / U(g_n) \\ &\rightarrow 0 \text{ as } n \rightarrow \infty. \end{aligned}$$

Likewise

$$\begin{aligned} \lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} P[|\gamma| > \delta] &\leq \lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} \delta^{-1} g_n^{-1} n |E Z_1^{-1} [|Z_1| > g_n]| \sum_{|j| > m} |c_j| \\ &= 0 \end{aligned}$$

as desired for the verification of (2.6).

Continuation of the proof of Proposition 2.3: From Proposition 2.4 we have (recall $\sigma^2 = E Z_1^2 = \text{Var}(Z_1)$)

$$\alpha_n^{-1} \sum_{t=1}^n \sum_{i=-\infty}^{\infty} c_i c_{i+h} (Z_{t-i}^2 - \sigma^2) \Rightarrow \left(\sum_{i=-\infty}^{\infty} c_i c_{i+h} \right) N$$

and hence from the analogue of Proposition 2.1

$$n a_n^{-2} (\hat{\gamma}(h) - \gamma(h)) \Rightarrow \left(\sum c_i c_{i+h} \right) N.$$

The assertion of Proposition 2.3 easily follows.

Remark. The same limit law holds if $\hat{\gamma}(h)$ is replaced by the mean corrected version.

$$\tilde{\gamma}(h) = \frac{1}{n} \sum_{t=1}^n (X_t - \bar{X})(X_{t+h} - \bar{X})$$

3. Sample covariance function of $\{Z_t\}$

Assume $\{Z_t\}$ is iid and satisfies (1.2) and (1.3) with $0 < \alpha < 2$. As before, define

$$(3.1) \quad a_n = \inf\{x: P(|Z_1| > x) \geq n^{-1}\}.$$

Applying Theorem 4.2 in Davis and Resnick (1984) to the Z_t sequence (i.e., take $c_j = 0, j \neq 0$ and $c_0 = 1$), we obtain

$$a_n^{-2} \sum_{t=1}^n Z_t Z_{t+h} \Rightarrow S \cdot 0 = 0 \text{ for all } h > 0$$

and

$$a_n^{-2} \sum_{t=1}^n Z_t^2 \Rightarrow S$$

where S is a positive stable random variable with index $\alpha/2$. In this section, we give a different normalization for the partial sums $\sum_{t=1}^n Z_t Z_{t+h}, h > 0$ in order to get a non-degenerate weak limit. Not surprisingly, these partial sums (i.e. sample covariances) at different lags turn out to be asymptotically independent. This will be the main building block for deriving the limit distribution of the sample correlation function of the X_t process in the next section.

Throughout this section we shall assume $E|Z_1|^\alpha = \infty$. It then follows from Theorem 3.3 (iv) in Cline (1983), that the product $Z_0 Z_1$ belongs to the α -domain of attraction. That is $Z_0 Z_1$ satisfies

$$(3.2) \quad \frac{P(|Z_0 Z_1| > tx)}{P(|Z_0 Z_1| > t)} \rightarrow x^{-\alpha} \quad \text{as } t \rightarrow \infty, x > 0$$

and

$$(3.3) \quad \frac{P(Z_0 Z_1 > t)}{P(|Z_0 Z_1| > t)} \rightarrow p^2 + (1-p)^2 \quad \text{as } t \rightarrow \infty$$

where p is given in (1.3).

Define

$$(3.4) \quad \tilde{a}_n = \inf\{x: P(|Z_0 Z_1| > x) \geq n^{-1}\}.$$

We first show that

$$(3.5) \quad \tilde{a}_n / a_n \rightarrow \infty.$$

Observe that for a fixed positive number M,

$$\begin{aligned} \frac{P(|Z_0 Z_1| > t)}{P(|Z_0| > t)} &\geq \frac{P(|Z_0| > t/|Z_1|, |Z_1| \leq M)}{P(|Z_0| > t)} \\ &= \int_0^M \frac{P(|Z_0| > t/y)}{P(|Z_0| > t)} P(|Z_1| \in dy). \end{aligned}$$

We then have by Fatou's Lemma and (1.2)

$$\liminf_{t \rightarrow \infty} \frac{P(|Z_0 Z_1| > t)}{P(|Z_0| > t)} \geq \int_0^M y^\alpha P(|Z_1| \in dy)$$

and upon letting $M \rightarrow \infty$, the lower bound converges to $E|Z_1|^\alpha = \infty$. It now is easy to check that (3.5) must hold.

The joint asymptotic behavior of the partial sums $(\sum_{t=1}^n Z_t^2, \sum_{t=1}^n Z_t Z_{t+1}, \dots, \sum_{t=1}^n Z_t Z_{t+h})$ is handled using point process techniques. For background on point processes, see Kallenberg (1976). Set $\chi_t = (Z_t, Z_t Z_{t+1}, \dots, Z_t Z_{t+h})$ for $t = 0, \pm 1, \pm 2, \dots$ and define $a_n^{-1} \chi_t = (a_n^{-1} Z_t, a_n^{-1} Z_t Z_{t+1}, \dots, a_n^{-1} Z_t Z_{t+h})$. The relevant sequence of point processes for this problem is given by

$$I_n = \sum_{t=1}^n \epsilon_{a_n^{-1} \chi_t}$$

which is defined on the state space $E = \mathbb{R}^{h+1} \setminus \{(0, 0, \dots, 0)\}$ where ϵ_x is the measure assigning unit mass to the point x and zero elsewhere. In defining a point process on E , we shall use the convention that if a point falls outside the state space it does not contribute to the sum. \mathcal{E} will denote the usual product σ -algebra on E modified so that the compact subsets of E are those compact sets in \mathbb{R}^{h+1} which are bounded away from $(0, 0, \dots, 0)$.

It will be shown that the sequence $\{I_n\}$ converges in distribution to a

Poisson process defined as follows: Let $\sum_{k=1}^{\infty} \epsilon_{j_k^{(1)}} \cdot \sum_{k=1}^{\infty} \epsilon_{j_k^{(2)}} \cdot \dots \cdot \sum_{k=1}^{\infty} \epsilon_{j_k^{(h)}}$

be h iid Poisson process on $\mathbb{R} \setminus \{0\}$ with intensity measure given by $\tilde{\lambda}(dx) =$

$\alpha_{\tilde{p}} x^{-\alpha-1} 1_{(0, \infty)}(x) dx + \alpha_{\tilde{q}} (-x)^{-\alpha-1} 1_{(-\infty, 0)}(x) dx$ where $\tilde{p} = p^2 + (1-p)^2$ and

$\tilde{q} = 1 - \tilde{p}$. Further let $\sum_{k=1}^{\infty} \epsilon_{j_k^{(0)}}$ also be a Poisson process on $\mathbb{R} \setminus \{0\}$ independent

of the h Poisson processes above with intensity $\lambda(dx) = \alpha p x^{-\alpha-1} 1_{(0, \infty)}(x) dx + \alpha q (-x)^{-\alpha-1} 1_{(-\infty, 0)}(x) dx$. The limit point process is then

$$I = \sum_{k=1}^{\infty} \sum_{i=0}^h \epsilon_{j_k^{(i)}} \cdot e_i$$

where $e_i \in \mathbb{R}^{h+1}$ is the basis element with i^{th} component equal to one and the rest zero. In other words, the points of I are located on the coordinate axes, the points $\{j_k^{(i)}, k = 1, 2, \dots\}$ lying on the axis determined by e_i .

In order to establish $I_n \Rightarrow I$ it is convenient to first specify a class of sets (as in Section 2 of Davis and Resnick, 1984) which generate \mathcal{E} . Let S be the collection of all sets B of the form

$$B = (b_0, c_0] \times (b_1, c_1] \times \dots \times (b_h, c_h]$$

which are bounded away from $(0, 0, \dots, 0)$ and $b_i < c_i$, $b_i \neq 0$, $c_i \neq 0$ for $i = 0, 1, \dots, h$. It is clear that S is a DC-semiring (cf. Kallenberg, 1976, p. 3). Moreover, since $B \in S$ is bounded away from zero, either

$$(C1) \quad B \cap \{y e_i : y \in \mathbb{R}\} = \emptyset \text{ for } i = 0, \dots, h$$

or

$$(C2) \quad B \cap \{y e_i : y \in \mathbb{R}\} = \begin{cases} (b_j, c_j] & i = j \\ \emptyset & i \neq j. \end{cases}$$

That is, B has either empty intersection with all of the coordinate axes or

intersects exactly one in an interval. Note that in (C2), $b_i < 0 < c_i$ for $i \neq j$

and $0 \notin (b_j, c_j]$. Further properties of these sets are developed in the following proposition.

Proposition 3.1.

- (i) $nP(a_n^{-1} X_1 \in B) \rightarrow 0$ if $B \in S$ satisfies C1.
- (ii) $nP(a_n^{-1} X_1 \in B) \rightarrow \begin{cases} \lambda(b_0, c_0] & \text{if } B \in S \text{ satisfies C2 with } j = 0 \\ \tilde{\lambda}(b_j, c_j] & \text{if } B \in S \text{ satisfies C2 with } j \neq 0. \end{cases}$
- (iii) $nP(a_n^{-1} X_1 \in B_1, a_n^{-1} X_t \in B_2) \rightarrow 0$ if B_1 and $B_2 \in S$ and $1 < t \leq 1+h$.
- (iv) $n^2 P(a_n^{-1} X_1 \in B_1, a_n^{-1} X_t \in B_2) \leq C$ for all n and $t > 1+h$ where

C is a constant depending only on the sets B_1 and B_2 in S .

Proof. (i) Setting $x^* = |b_0| \wedge |c_0| > 0$ and $y^* = |b_1| \wedge |c_1| > 0$, we have

$$\begin{aligned} nP(a_n^{-1} X_1 \in B) &\leq nP(|Z_1| > a_n x^*, |Z_1 Z_2| > \tilde{a}_n y^*) \\ &\leq nP(|Z_1| > a_n M) \\ &\quad + nP(|Z_1| > a_n x^*, |Z_1 Z_2| > \tilde{a}_n y^*, |Z_1| \leq a_n M) \end{aligned}$$

From (1.2) and (3.1) we have $nP(|Z_1| > a_n M) \rightarrow M^{-\alpha}$ as $n \rightarrow \infty$ which can be made arbitrarily small by choosing M large. The second term is bounded by

$$\begin{aligned} nP(|Z_1| > a_n x^*, |Z_2| > \frac{\tilde{a}_n y^*}{a_n M}) &\leq nP(|Z_1| > a_n x^*) P(|Z_2| > \frac{\tilde{a}_n y^*}{a_n M}) \\ &\rightarrow (x^*)^{-\alpha} \cdot 0 = 0 \end{aligned}$$

since $\tilde{a}_n/a_n \rightarrow \infty$ by (3.5).

(ii) Suppose $j = 0$. Then, with $x^* = |b_0| \wedge |c_0|$, $y^* = \min_{1 \leq i \leq h} (|b_i| \wedge |c_i|) > 0$

and using an elementary bound, we have

$$\begin{aligned} |nP(a_n^{-1} X_1 \in B) - nP(a_n b_0 < Z_1 \leq a_n c_0)| \\ \leq nhP(|Z_1| > a_n x^*, |Z_1 Z_2| > \tilde{a}_n y^*) \end{aligned}$$

which goes to zero as $n \rightarrow \infty$ by the proof in (i). Moreover, it follows from (1.2) and (1.3) that $nP(a_n b_o < Z_1 \leq a_n c_o) \rightarrow \lambda(b_o, c_o]$. The argument for the case $j \neq 0$ is handled in the same manner and is omitted.

(iii) If either B_1 or B_2 satisfies C1, then we are done by (i). So suppose B_1 and B_2 satisfy C2 with $B_1 \cap \mathcal{E}_j = (b_j^{(1)}, c_j^{(1)})] \neq \emptyset$, $B_2 \cap \mathcal{E}_{j'} = (b_{j'}^{(2)}, c_{j'}^{(2)})] \neq \emptyset$. Then if $j \neq 0$ and $j' \neq 0$,

(3.6) $nP(a_n^{-1} Y_1 \in B_1, a_n^{-1} Y_t \in B_2) \leq nP(|Z_1 Z_{1+j}| > \tilde{a}_n x^*, |Z_t Z_{t+j}| > \tilde{a}_n y^*)$
 where $x^* = |b_j^{(1)}| \wedge |c_j^{(1)}|$ and $y^* = |b_{j'}^{(2)}| \wedge |c_{j'}^{(2)}|$. Now if $t \neq 1+j$ and $t+j' \neq 1+j$, then by independence

$$\begin{aligned} nP(|Z_1 Z_{1+j}| > \tilde{a}_n x^*, |Z_t Z_{t+j}| > \tilde{a}_n y^*) \\ = nP(|Z_1 Z_{1+j}| > \tilde{a}_n x^*) P(|Z_t Z_{t+j}| > \tilde{a}_n y^*) \\ \rightarrow 0. \end{aligned}$$

On the other hand if $t = 1+j$ or $t+j' = 1+j$, then we have the bound

$$\begin{aligned} nP(|Z_1 Z_2| > \tilde{a}_n x^*, |Z_2 Z_3| > \tilde{a}_n y^*) \\ \leq nP(|Z_2| > a_n M) \\ + nP(|Z_1 Z_2| > \tilde{a}_n x^*, |Z_2 Z_3| > \tilde{a}_n y^*, |Z_2| \leq a_n M) \\ \leq nP(|Z_2| > a_n M) + nP(|Z_1 Z_2| > \tilde{a}_n x^*) P(|Z_3| > \frac{\tilde{a}_n}{a_n M} y^*) \\ \rightarrow M^{-\alpha} \text{ as } n \rightarrow \infty \end{aligned}$$

where we have used (3.5) in the second term. Since M is arbitrary the left side of (3.6) must have a zero limit. The other cases $j = 0$ or $j' = 0$ are done in a similar way.

(iv) This follows easily from (i) and (ii) since for $t > 1+h$ the vectors Y_1 and Y_t are independent. \square

Proposition 3.2 Let $\{Z_i\}$ be iid satisfying (1.2), (1.3) with $0 < \alpha < 2$ and suppose $E |Z_1|^\alpha = \infty$. If a_n, \tilde{a}_n are given by (3.1), (3.4) we have

$$I_n \Rightarrow I$$

in the sense of convergence of point processes on the space E (cf. Kallenberg, 1976).

Proof. Since the point process I is simple, it suffices to show by Theorem 4.7 in Kallenberg (1976) that

$$(3.7) \quad E I_n(B) \rightarrow E I(B) < \infty \text{ for all } B \in S$$

and

$$(3.8) \quad P(I_n(R) = 0) \rightarrow P(I(R) = 0) \text{ for all sets } R \text{ which are a finite union of disjoint sets in } S.$$

Clearly (3.7) is automatic from (i) and (ii) of Proposition 3.1 because I has all of its points on the coordinate axes. Now suppose $R = \bigcup_{j=1}^m B_j$ is a union of disjoint sets in S . For a fixed positive integer k , define $I_{[n/k]}^*(R) = \sum_{t=1}^{[n/k]} \epsilon_{\lambda_n^{-1} \gamma_t} (R)$ where $[x]$ is the greatest integer $\leq x$. Using a Bonferroni-type

inequality, stationarity and the disjointness of the sets B_j , we have

$$\begin{aligned} \sum_{j=1}^m [n/k] P(\lambda_n^{-1} \gamma_1 \in B_j) &= \sum_{i=1}^m \sum_{j=1}^m \sum_{t=2}^{[n/k]} [n/k] P(\lambda_n^{-1} \gamma_1 \in B_i, \lambda_n^{-1} \gamma_t \in B_j) \\ &\leq P(I_{[n/k]}^*(R) > 0) \leq \sum_{j=1}^m [n/k] P(\lambda_n^{-1} \gamma_1 \in B_j). \end{aligned}$$

It follows from above that

$$\sum_{j=1}^m [n/k] P(\lambda_n^{-1} \gamma_1 \in B_j) = E I_{[n/k]}^*(R) \rightarrow k^{-1} E I(R)$$

as $n \rightarrow \infty$. Applying Proposition 3.1 (iii) and (iv), we also have

$$\limsup_{n \rightarrow \infty} \sum_{t=2}^{[n/k]} [n/k] P(\lambda_n^{-1} \gamma_1 \in B_i, \lambda_n^{-1} \gamma_t \in B_j) = o(1/k) \text{ as } k \rightarrow \infty$$

for $i, j = 1, \dots, m$ so that

$$(3.9) \quad 1 - k^{-1} E I(R) \leq \liminf_{n \rightarrow \infty} P(I_{[n/k]}^*(R) = 0) \\ \leq \limsup_{n \rightarrow \infty} P(I_{[n/k]}^*(R) = 0) \leq 1 - k^{-1} E I(R) + o(1/k)$$

Since the vector-valued process X_t is h -dependent, a standard argument (cf. Leadbetter, Lindgren, and Rootzén, 1983, chapters 3 and 5) gives

$$(3.10) \quad P^k(I_{[n/k]}^*(R) = 0) = P(I_n(R) = 0) \rightarrow 0 \text{ as } n \rightarrow \infty$$

for every positive integer k . Taking the k^{th} power of (3.9) and using (3.10), we obtain

$$(1 - k^{-1} E I(R))^k \leq \liminf_{n \rightarrow \infty} P(I_n(R) = 0) \leq \limsup_{n \rightarrow \infty} P(I_n(R) = 0) \\ \leq (1 - k^{-1} E I(R) + o(1/k))^k.$$

Now letting $k \rightarrow \infty$, we have $P(I_n(R) = 0) \rightarrow e^{-E I(R)}$. But I is a Poisson process so that $e^{-E I(R)} = P(I(R) = 0)$ which verifies (3.8) as desired. \square

Theorem 3.3. Let $\{Z_t\}$ be iid satisfying (1.2) and (1.3) with $0 < \alpha < 2$ and $E|Z_1|^\alpha = \infty$. Then, if a_n and \tilde{a}_n are given by (3.1) and (3.4),

$$(a_n^{-2} \sum_{t=1}^n Z_t^2, \tilde{a}_n^{-1} \sum_{t=1}^n (Z_t Z_{t+1} - \mu_n), \dots, \tilde{a}_n^{-1} \sum_{t=1}^n (Z_t Z_{t+h} - \mu_n)) \\ \Rightarrow (S_0, S_1, \dots, S_h)$$

where $\mu_n = E Z_1 Z_2 1_{[|Z_1 Z_2| \leq \tilde{a}_n]}$ and S_0, S_1, \dots, S_h are independent stable random variables; S_0 is positive with index $\alpha/2$ and S_1, S_2, \dots, S_h are identically distributed with index α .

Proof. Adapting the argument used in Section 2 of Resnick (1984) and in Section 4 of Davis and Resnick (1984) (see also Resnick and Greenwood, 1978) it is easy to show, for any $0 < \delta < 1$,

$$(a_n^{-2} \sum_{t=1}^n Z_t^2 1_{[|Z_t| > a_n \delta]}, \tilde{a}_n^{-1} \sum_{t=1}^n (Z_t Z_{t+i} 1_{[|Z_t Z_{t+j}| > \tilde{a}_n \delta]} - \\ E Z_1 Z_2 1_{[\tilde{a}_n \delta < |Z_1 Z_2| \leq \tilde{a}_n]}), 1 \leq i \leq h)$$

$$\Rightarrow (S_0^\delta, S_1^\delta, \dots, S_h^\delta)$$

$$\text{where } S_0^\delta = \sum_{k=1}^{\infty} (j_k^{(0)})^2 \mathbf{1}_{[|j_k^{(0)}| > \delta]} \text{ and } S_i^\delta = \sum_{k=1}^{\infty} j_k^{(i)} \mathbf{1}_{[|j_k^{(i)}| > \delta]}$$

- $\int_{|s| \in (\delta, 1]} s \tilde{\lambda}(ds)$ for $i = 1, 2, \dots, h$. Clearly, $S_0^\delta, S_1^\delta, \dots, S_h^\delta$ are independent

since the points $\{j_k^{(0)}\}, \{j_k^{(1)}\}, \dots, \{j_k^{(h)}\}$ are independent. The Ito representation implies $S_i^\delta \Rightarrow S_i$ as $\delta \rightarrow 0$, $i = 0, 1, \dots, h$ (cf. Resnick, 1984) where the vector (S_0, S_1, \dots, S_h) is as described in the statement of the theorem. In view of Billingsley (1968), Theorem 4.2, the proof is complete once we show

$$(3.11) \quad \lim_{\delta \rightarrow 0} \limsup_{n \rightarrow \infty} E(a_n^{-2} \sum_{t=1}^n Z_t^2 \mathbf{1}_{[|Z_t| \leq a_n \delta]}) = 0.$$

and

$$(3.12) \quad \lim_{\delta \rightarrow 0} \limsup_{n \rightarrow \infty} \text{Var}(\hat{a}_n^{-1} \sum_{t=1}^n Z_t Z_{t+1} \mathbf{1}_{[|Z_t Z_{t+1}| \leq \hat{a}_n \delta]}) = 0, i = 1, \dots, h.$$

The expectation in (3.11) is equal to $\frac{n}{a_n^2} E Z_1^2 \mathbf{1}_{[|Z_1| \leq a_n \delta]}$ which has the desired

limit by Karamata's Theorem (Feller, 1971, p. 283). Since the process

$\{Z_t Z_{t+1}, t = 0, \pm 1, \pm 2, \dots\}$ is 1-dependent, (3.12) holds by the comment on the top of p. 266, Davis (1983). \square

Remarks.

- 1) If the distribution of Z_t is symmetric then so is the distribution of $Z_t Z_{t+1}$ in which case $\mu_n = 0$.
- 2) For $0 < \alpha < 1$, the theorem remains valid without centering the terms $Z_t Z_{t+1}$ by μ_n .

- 3) In the case $1 < \alpha < 2$, $E Z_1 Z_2 = (E Z_1)^2$ exists and from Karamata's Theorem, $n^{\alpha-2} (E(Z_1 Z_2) - \mu_n) = n^{\alpha-2} E(Z_1 Z_2 1_{[|Z_1 Z_2| > \frac{1}{n}]}) \rightarrow \text{const.}$ Thus, by the convergence of types result, Theorem 3.3 is also valid if μ_n is replaced by $\mu^2 = (E Z_1)^2$.

4. Sample correlation function of $\{X_t\}$

As before let $\{Z_t\}$ be iid satisfying (1.2) and (1.3) with $0 < \alpha < 2$, $E |Z_t|^\alpha = \infty$, and define

$$(4.1) \quad X_t = \sum_{j=-\infty}^{\infty} c_j Z_{t-j}$$

where

$$(4.2) \quad \sum_{j=-\infty}^{\infty} |c_j|^\delta |j| < \infty \quad \text{with} \quad \begin{cases} \delta = 1 & \text{if } \alpha > 1 \\ 0 < \delta < \alpha & \text{if } \alpha \leq 1. \end{cases}$$

We shall first concentrate on the unadjusted sample correlation function defined by

$$(4.3) \quad \hat{\rho}(h) = \frac{C(h)}{C(0)}, \quad h \geq 0$$

where

$$(4.4) \quad C(h) = \sum_{t=1}^n X_t X_{t+h}.$$

The sum in (4.4) is terminated at n rather than $n - h$ for notational simplicity in the following arguments. All of the results in this section, however, remain valid if the upper limit is $n - h$. Put $\rho(h) = \sum_j c_j c_{j+h} / \sum_j c_j^2$, which in the case

that $\text{Var}(Z_t) < \infty$, is equal to $\text{Corr}(X_t, X_{t+h})$. In Davis and Resnick, 1984, Theorem 4.2 it was shown under condition (1.4) that $\hat{\rho}(h) \xrightarrow{P} \rho(h)$. Here, we consider the limit distribution of $\hat{\rho}(h)$, suitably normalized. We begin with the following proposition which is similar to Lemma 8.4.3 in Anderson (1971).

Proposition 4.1. Assume (4.1), (4.2) and $E|Z_1|^\alpha = \infty$. Then for every positive integer h ,

$$(4.5) \quad \tilde{a}_n^{-1} a_n^2 (\hat{\rho}(h) - \rho(h) - [C(0)]^{-1} \sum_{t=1}^n \sum_{\substack{i,j \\ i \neq j}} c_i (c_{j+h} - c_j \rho(h)) Z_{t-i} Z_{t-j}) \xrightarrow{P} 0$$

where a_n and \tilde{a}_n are given by (3.1) and (3.4), respectively.

Proof. We have

$$\begin{aligned} \hat{\rho}(h) - \rho(h) &= [C(0)]^{-1} (C(h) - \rho(h)C(0)) \\ &= [C(0)]^{-1} \sum_{t=1}^n \left(\sum_i \sum_j c_i c_j Z_{t-i} Z_{t+h-j} - \rho(h) \sum_i \sum_j c_i c_j Z_{t-i} Z_{t-j} \right) \\ &= [C(0)]^{-1} \sum_{t=1}^n \sum_i \sum_j c_i (c_{j+h} - c_j \rho(h)) Z_{t-i} Z_{t-j} \end{aligned}$$

so that the difference in (4.5) is equal to

$$\begin{aligned} \tilde{a}_n^{-1} a_n^2 [C(0)]^{-1} \sum_{t=1}^n \sum_i (c_i c_{i+h}^2 - c_i^2 \rho(h)) Z_{t-i}^2 \\ = \tilde{a}_n^{-1} a_n^2 [C(0)]^{-1} \sum_i ((c_i c_{i+h} - c_i^2 \rho(h)) \sum_{t=1}^n Z_{t-i}^2) \\ = \tilde{a}_n^{-1} a_n^2 [C(0)]^{-1} \sum_i (c_i c_{i+h} - c_i^2 \rho(h)) \left(\sum_{t=1}^n Z_t^2 + U_{n,i} \right) \end{aligned}$$

where $U_{n,i} = \sum_{t=1-i}^{n-i} Z_t^2 - \sum_{t=1}^n Z_t^2$ is the sum of at most $2i$ random variables. Since

$a_n^{-2} C(0)$ converges in distribution (Theorem 4.2 in Davis and Resnick, 1984) and

$\sum_i (c_i c_{i+h} - c_i^2 \rho(h)) = 0$ it suffices to show

$$(4.6) \quad \limsup_{n \rightarrow \infty} E \left| \sum_i (c_i c_{i+h} - c_i^2 \rho(h)) U_{n,i} \right|^{\delta/2} < \infty,$$

δ defined in (4.2). Because $\delta < \alpha$, $E|Z_1|^\delta < \infty$, so that by the triangle inequality and assumption (4.2), we have

$$\begin{aligned}
 & E \left| \sum_i (c_i c_{i+h} - c_i^2 \rho(h)) U_{n,i} \right|^{\delta/2} \\
 & \leq \sum_i (|c_i c_{i+h}|^{\delta/2} + |c_i|^\delta |\rho(h)|^{\delta/2}) E |U_{n,i}|^{\delta/2} \\
 & \leq \sum_i (|c_i c_{i+h}|^{\delta/2} + |c_i|^\delta |\rho(h)|^{\delta/2}) (2 |i| E |Z_1|^\delta)
 \end{aligned}$$

and by the Schwartz Inequality this is bounded by

$$\begin{aligned}
 & \leq 2 E |Z_1|^\delta \left[\left(\sum_i |c_i|^\delta |i| \right)^{1/2} \left(\sum_i |c_{i+h}|^\delta |i| \right)^{1/2} + |\rho(h)|^{\delta/2} \left(\sum_i |c_i|^\delta |i| \right) \right] \\
 & < \infty
 \end{aligned}$$

by assumption 4.2. Thus (4.6) follows since the bound does not depend on n . \square

Proposition 4.2. Assume (4.1), (4.2) and $E |Z_1|^\alpha = \infty$. Then

$$(4.6) \quad a_n^{-2} (C(0) - \sum_{t=1}^n \sum_{i=-\infty}^{\infty} c_i Z_{t-i}^2) = a_n^{-2} \sum_{t=1}^n \sum_{\substack{i,j \\ i \neq j}} c_i c_j Z_{t-i} Z_{t-j} \xrightarrow{P} 0.$$

Proof. The proof of Proposition 2.1 can be adapted to this case but a simpler argument is given here instead. Choose $0 < \delta < \alpha$ satisfying (4.2) with $\alpha < 2\delta$. The triangle inequality gives

$$\begin{aligned}
 & E |a_n^{-2} \sum_{t=1}^n \sum_{\substack{i,j \\ i \neq j}} c_i c_j Z_{t-i} Z_{t-j}|^\delta \\
 & \leq a_n^{-2\delta} n \sum_{\substack{i,j \\ i \neq j}} |c_i c_j|^\delta E |Z_1 Z_2|^\delta \\
 & \leq n a_n^{-2\delta} \left(\sum_i |c_i|^\delta \right)^2 (E |Z_1|^\delta)^2.
 \end{aligned}$$

Now since a_n is regularly varying with index $1/\alpha$, $a_n^{2\delta}$ is regularly varying with index $2\delta/\alpha > 1$, and hence $n a_n^{-2\delta} \rightarrow 0$. \square

Rearranging the terms in the sum (4.5), we have

$$\begin{aligned}
 \sum_{t=1}^n \sum_{\substack{i,j \\ i \neq j}} c_i (c_{j+h} - c_j \rho(h)) Z_{t-i} Z_{t-j} &= \sum_{t=1}^n \sum_i \sum_{j \neq 0} c_i (c_{i-j+h} - c_{i-j} \rho(h)) Z_{t-i} Z_{t-i+j} \\
 (4.7) \qquad \qquad \qquad &= \sum_{j \neq 0} \sum_{t=1}^n \sum_i \psi_{i,j} Z_{t-i} Z_{t-i+j}
 \end{aligned}$$

where $\psi_{i,j} = c_i (c_{i-j+h} - c_{i-j} \rho(h))$, $i = 0, \pm 1, \pm 2, \dots$, $j = \pm 1, \pm 2, \dots$

Proposition 4.3. Assume (4.1), (4.2) and $E|Z_1|^\alpha = \infty$. As $n \rightarrow \infty$ we have

$$\begin{aligned}
 (i) \quad a_n^{-1} \left(\sum_{t=1}^n \left(\sum_i \psi_{i,j} Z_{t-i} Z_{t-i+j} + \sum_i \psi_{i,-j} Z_{t-i} Z_{t-i-j} \right) \right. \\
 \left. - \sum_i (\psi_{i,j} + \psi_{i,-j}) \sum_{t=1}^n Z_t Z_{t+j} \right) \xrightarrow{P} 0
 \end{aligned}$$

for each $j > 0$ and

$$(ii) \quad a_n^{-2} \left(\sum_{t=1}^n \sum_i c_i^2 Z_{t-i}^2 - \sum_i c_i^2 \sum_{t=1}^n Z_t^2 \right) \xrightarrow{P} 0$$

and therefore $a_n^{-2} (C(0) - \sum_i c_i^2 \sum_{t=1}^n Z_t^2) \xrightarrow{P} 0$.

Proof. (i) Interchanging the order of summation and regrouping terms, the difference in (i) becomes

$$\begin{aligned}
 a_n^{-1} \sum_i \psi_{i,j} \left(\sum_{t=1-i}^{n-i} Z_t Z_{t+j} - \sum_{t=1}^n Z_t Z_{t+j} \right) + a_n^{-1} \sum_i \psi_{i,-j} \left(\sum_{t=1-i-j}^{n-i-j} Z_t Z_{t+j} - \sum_{t=1}^n Z_t Z_{t+j} \right) \\
 = a_n^{-1} \sum_i \psi_{i,j} V_{n,i} + a_n^{-1} \sum_i \psi_{i,-j} W_{n,i}
 \end{aligned}$$

where $V_{n,i} = \sum_{t=1-i}^{n-i} Z_t Z_{t+j} - \sum_{t=1}^n Z_t Z_{t+j}$ and $W_{n,i} = \sum_{t=1-i-j}^{n-i-j} Z_t Z_{t+j} - \sum_{t=1}^n Z_t Z_{t+j}$.

However with δ as chosen in (4.2)

$$\begin{aligned} \limsup_n E \left| \sum_j \psi_{1,j} V_{n,i} \right|^\delta &\leq \limsup_n \sum_i |\psi_{1,j}|^\delta E |V_{n,i}|^\delta \\ &\leq 2 \sum_i |\psi_{1,j}|^\delta |1| E |Z_1|^\delta |Z_2|^\delta < \infty \end{aligned}$$

whence $\tilde{a}_n^{-1} \sum_i \psi_{1,j} V_{n,i} \xrightarrow{P} 0$. The same argument also gives $\tilde{a}_n^{-1} \sum_i \psi_{1,-j} W_{n,i} \xrightarrow{P} 0$

which proves (i).

(ii) The above argument also works in this case but with δ replaced by $\delta/2$. The last statement follows from Proposition 4.2. \square

Theorem 4.4. Suppose $X_t = \sum_{j=-\infty}^{\infty} c_j Z_{t-j}$ where $\{c_j\}$ satisfies (4.2) and $\{Z_t\}$

satisfies (1.2), (1.3) and $E|Z_1|^\alpha = \infty$, $0 < \alpha < 2$. If a_n and \tilde{a}_n are given by (3.1) and (3.4), then for any positive integer ℓ ,

$$(4.8) \quad (\tilde{a}_n^{-1} a_n^2 (\hat{\rho}(h) - \rho(h) - d_{h,n}/C(0)), 1 \leq h \leq \ell) \Rightarrow (Y_1, Y_2, \dots, Y_\ell)$$

in \mathbb{R}^ℓ , where $d_{h,n} = \sum_{j=1}^{\infty} (\rho(h+j) + \rho(h-j) - 2\rho(j)\rho(h)) \sum_i c_i^2 E Z_1 Z_2 1_{[|Z_1 Z_2| \leq \tilde{a}_n]}$,

$Y_h = \sum_{j=1}^{\infty} (\rho(h+j) + \rho(h-j) - 2\rho(j)\rho(h)) S_j / S_0$ and S_0, S_1, S_2, \dots are independent

stable random variables as described in Theorem 3.3 (i.e. S_0 is positive with index $\alpha/2$ and S_1, S_2, \dots are identically distributed with index α). In addition if either

- (i) $0 < \alpha < 1$ or
- (ii) $\alpha = 1$ and the distribution of Z_t is symmetric or
- (iii) $1 < \alpha < 2$ and $E Z_1 = 0$

then (4.8) holds with $d_{h,n} = 0$, $h = 1, \dots, \ell$ and a location change in the S_j 's, $j \geq 1$.

Observe that since both a_n and \tilde{a}_n are regularly varying with index $1/\alpha$, the normalization a_n^2/\tilde{a}_n is also regularly varying with index $1/\alpha$. That is,

$a_n^2/\tilde{a}_n = n^{1/\alpha} \tilde{\gamma}(n)$ for some slowly varying function $\tilde{\gamma}$.

Proof. From Proposition 4.3, Theorem 3.3, and the continuous mapping theorem, we have for any fixed positive integer m ,

$$(4.9) \quad (a_n^{-2} C(0), \tilde{a}_n^{-1} \sum_{0 < |j| \leq m} \sum_{t=1}^n (\sum_{i=1}^{\infty} \psi_{i,j} (Z_{t-i} Z_{t-i+j} - \mu_n))) \\ \Rightarrow (\sum_{i=1}^{\infty} c_i^2 S_0, \sum_{j=1}^m \sum_{i=1}^{\infty} (\psi_{i,j} + \psi_{i,-j}) S_j)$$

where $\mu_n = E Z_1 Z_2^{-1} [Z_1 Z_2^{-1} \leq \tilde{a}_n]$. The dependence of $\psi_{i,j}$ on h is temporarily suppressed. The plan of the proof is to first show that (4.9) remains valid with m replaced by ∞ and then make use of Propositions 4.1 - 4.3 to derive the weak limit of $\tilde{a}_n^{-1} a_n^2 (\hat{\rho}(h) - \rho(h) - d_{h,n}/C(0))$.

To establish the limit in (4.9) with m replaced by ∞ it suffices to show (cf. Billingsley, 1968, Theorem 4.2) that

$$(4.10) \quad \lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} P(\tilde{a}_n^{-1} |\sum_{|j| > m} \sum_{t=1}^n \sum_{i=1}^{\infty} \psi_{i,j} (Z_{t-i} Z_{t-i+j} - \mu_n)| > \gamma) = 0$$

for every $\gamma > 0$ and

$$(4.11) \quad \sum_{j=1}^m \sum_{i=1}^{\infty} (\psi_{i,j} + \psi_{i,-j}) S_j \Rightarrow \sum_{j=1}^{\infty} \sum_{i=1}^{\infty} (\psi_{i,j} + \psi_{i,-j}) S_j.$$

The limit in (4.11) can be checked using characteristic functions since

$\sum_{j=1}^{\infty} |\sum_{i=1}^{\infty} (\psi_{i,j} + \psi_{i,-j})|^\alpha < \infty$. As for (4.10), we have the bound

$$P(\tilde{a}_n^{-1} |\sum_{|j| > m} \sum_{t=1}^n \sum_{i=1}^{\infty} \psi_{i,j} (Z_{t-i} Z_{t-i+j} - \mu_n)| > \gamma) \\ \leq P(\tilde{a}_n^{-1} |\sum_{|j| > m} \sum_{t=1}^n \sum_{i=1}^{\infty} \psi_{i,j} (Z_{t-i} Z_{t-i+j}^{-1} [Z_{t-i} Z_{t-i+j}^{-1} \leq \tilde{a}_n] - \mu_n)| > \gamma/2) \\ + P(\tilde{a}_n^{-1} |\sum_{|j| > m} \sum_{t=1}^n \sum_{i=1}^{\infty} \psi_{i,j} Z_{t-i} Z_{t-i+j}^{-1} [Z_{t-i} Z_{t-i+j}^{-1} > \tilde{a}_n]| > \gamma/2) \\ = A + B.$$

Applying Chebyshev's inequality to A gives, after some simplification, (see the proof of Proposition 2.1),

$$A \leq 4\gamma^{-2} a_n^{-2} \sum_{s=1}^n \sum_{t=1}^n \sum_i \sum_{|j|>m} \sum_{|j'|>m} |\psi_{i,j}| (|\psi_{s-t+i,j'}| + |\psi_{s-t+i-j,j'}| + |\psi_{s-t+i+j',j'}| + |\psi_{s-t+i-j+j',j'}|) \sigma_n^2$$

where $\sigma_n^2 = E|Z_1 Z_2|^2 1_{[|Z_1 Z_2| \leq \tilde{a}_n]}$. A change of variables in the summation gives the bound

$$A \leq 4\gamma^{-2} a_n^{-2} \sum_{t=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} \sum_{|j|>m} \sum_{|j'|>m} |\psi_{i,j}| (|\psi_{t+i,j'}| + |\psi_{t+i-j,j'}| + |\psi_{t+i+j',j'}| + |\psi_{t+i-j+j',j'}|) \sigma_n^2$$

and since $\sum_{t=-\infty}^{\infty} |\psi_{t+k,j'}| = \sum_{t=-\infty}^{\infty} |\psi_{t,j'}|$ for all integers k ,

$$A \leq 4\gamma^{-2} a_n^{-2} n 4 \left(\sum_{i=-\infty}^{\infty} \sum_{|j|>m} |\psi_{i,j}| \right)^2 \sigma_n^2.$$

The absolute summability of the c_j 's ensures that all of the above sums involving $|\psi_{i,j}|$ are finite and in particular $\lim_{m \rightarrow \infty} \sum_{|j|>m} \sum_{i=-\infty}^{\infty} |\psi_{i,j}| = 0$. Thus by Karamata's

Theorem ($\tilde{a}_n^{-2} n \sigma_n^2 \rightarrow \alpha/(2-\alpha)$), we have $\lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} A = 0$.

With δ as given in (4.2)

$$B \leq 2^\delta \gamma^{-\delta} a_n^{-\delta} n \sum_{|j|>m} \sum_i |\psi_{i,j}|^\delta E|Z_1 Z_2|^\delta 1_{[|Z_1 Z_2| > \tilde{a}_n]}$$

and again by Karamata's Theorem, $n \tilde{a}_n^{-\delta} E|Z_1 Z_2|^\delta 1_{[|Z_1 Z_2| > \tilde{a}_n]} \rightarrow \alpha/(\alpha - \delta)$

so that $\lim_{m \rightarrow \infty} \limsup_{n \rightarrow \infty} B = 0$ which established (4.9) with m replaced by ∞ .

Now from Proposition 4.1 and (4.7), we have

$$\tilde{a}_n^{-1} a_n^2 (\hat{o}(h) - o(h)) = \tilde{a}_n^{-1} a_n^2 (C(0))^{-1} \sum_{i \neq 0} \sum_{r=1}^n \sum_i \psi_{i,j} Z_{t-i} Z_{t-i+j} + o_p(1).$$

Since $\sum_i (\psi_{i,j} + \psi_{i,-j}) / \sum_i c_i^2 = \rho(h+j) + \rho(h-j) - 2\rho(j)\rho(h)$, we then have

$$\begin{aligned} & \tilde{a}_n^{-1} a_n^2 (\hat{\rho}(h) - \rho(h) - d_{h,n}/C(0)) \\ &= \tilde{a}_n^{-1} a_n^2 (C(0))^{-1} \sum_{j \neq 0} \sum_{t=1}^n \sum_i \psi_{i,j} (Z_{t-1} Z_{t-1+j} - \mu_n) + o_p(1). \end{aligned}$$

It follows by applying the continuous mapping theorem to (4.9) that

$$\begin{aligned} \tilde{a}_n^{-1} a_n^2 (\hat{\rho}(h) - \rho(h) - d_{h,n}/C(0)) &\Rightarrow \left(\sum_{j=1}^{\infty} \sum_i (\psi_{i,j} + \psi_{i,-j}) S_j / \sum_i c_i^2 S_0 \right) \\ &= Y_h. \end{aligned}$$

The proof of the joint convergence in (4.8) is essentially the same as the above argument. The only difference is that the vector in (4.9) is extended to an $l+1$ -dimensional vector where the $(h+1)^{th}$ component is given by

$$\tilde{a}_n^{-1} \sum_{0 < |j| < m} \sum_{t=1}^n \sum_i \psi_{i,j}^{(h)} (Z_{t-1} Z_{t-1+j} - \mu_n), \quad h = 1, 2, \dots, l.$$

Finally, the last statement of the theorem is an immediate consequence of Remarks 1 - 3 in Section 3. \square

In the following two results, we consider the limit laws of the mean corrected version of the sample correlation function defined by

$$\tilde{\rho}(h) = \frac{\sum_{t=1}^n (X_t - \bar{X})(X_{t+h} - \bar{X})}{\sum_{t=1}^n (X_t - \bar{X})^2}$$

where $\bar{X} = \frac{1}{n} \sum_{t=1}^n X_t$.

Corollary 1. Suppose $1 < \alpha < 2$. Then for any positive integer l ,

$$(\tilde{a}_n^{-1} a_n^2 (\tilde{\rho}(h) - \rho(h)), 1 \leq h \leq l) \Rightarrow (Y_1, Y_2, \dots, Y_l).$$

Proof. Since the function $\tilde{\rho}(h)$ is location invariant, we may assume without loss of generality that $E Z_t = 0$ (otherwise consider the process $X_t - E X_t =$

$\sum_{j=-\infty}^{\infty} c_j (Z_{t-j} - E Z_{t-j})$). In view of Theorem 4.4, it suffices to show

$\tilde{\rho}(h) - \hat{\rho}(h) = o_p(\hat{a}_n a_n^{-2})$. Using the identity $\sum_{t=1}^n X_t^2 - \sum_{t=1}^n (X_t - \bar{X})^2 = n \bar{X}^2$,

we have

$$(4.12) \quad \tilde{\rho}(h) - \hat{\rho}(h) = (\hat{\rho}(h)n \bar{X}^2 - \bar{X} \sum_{t=1}^n X_{t+h}) / \sum_{t=1}^n (X_t - \bar{X})^2.$$

In Section 4 of Davis and Resnick (1984), it was shown that $\sum_{t=1}^n (X_t - \bar{X})^2 = O_p(a_n^2)$,

$\sum_{t=1}^n X_t = O_p(a_n) = o_p(\hat{a}_n)$ and $\hat{\rho}(h) \xrightarrow{P} \rho(h)$. Since $\bar{X} \rightarrow E X_1 = 0$ and $\sum_{t=1}^n X_{t+h}/n \rightarrow E X_1 = 0$

a.s. by the ergodic theorem, this implies $\tilde{\rho}(h) - \hat{\rho}(h) = o_p(\hat{a}_n a_n^{-2})$ as desired. \square

In the $0 < \alpha < 1$ case, the sample mean plays a dominant role in determining the limit distribution of $\tilde{\rho}(h)$. In order to describe this result, it is necessary to first define two random variables. Let $\{j_k: k = 1, 2, \dots\}$ be the points of a Poisson process on $\mathbb{R} \setminus \{0\}$ with intensity $\lambda(dx) = \alpha p x^{-\alpha-1} 1_{(0, \infty)}(x) dx + \alpha q (-x)^{-\alpha-1} 1_{(-\infty, 0)}(x) dx$ where p and q are given in (1.2). Now if $0 < \alpha < 1$, then

$\sum_{k=1}^{\infty} |j_k| < \infty$ a.s. so that the random variables $S = \sum_{k=1}^{\infty} j_k$ and $S_0 = \sum_{k=1}^{\infty} j_k^2$ are

well-defined. In particular, S and S_0 each have a stable distribution with index α and $\alpha/2$ respectively.

Corollary 2. Suppose $0 < \alpha < 1$. Then for any positive integer ℓ

$$(n(\tilde{\rho}(h) - \rho(h)), 1 \leq h \leq \ell) \Rightarrow ((\rho(h) - 1), 1 \leq h \leq \ell) \left(\sum_i c_i \right)^2 S^2 / \left(\sum_i c_i^2 S_0 \right)$$

Remark. Some properties of the distribution function of S^2/S_0 are studied in Logan et al (1973). See also Cline (1983).

Proof. Let $\{j_k\}$ be the points of a Poisson process as described above. Using an argument similar to that given in Section 4 of Davis and Resnick (1984) (see also Resnick, 1984, Section 4) it is easy to show

$$(4.13) \quad (a_n^{-1} \sum_{t=1}^n X_t, a_n^{-2} \sum_{t=1}^n (X_t - \bar{X})^2) \Rightarrow ((\sum_1^{\infty} c_i) (\sum_{k=1}^{\infty} j_k), (\sum_1^{\infty} c_i^2) (\sum_{k=1}^{\infty} j_k^2)) \\ = ((\sum_1^{\infty} c_i) S, (\sum_1^{\infty} c_i^2) S_0).$$

Now rearranging the identity in (4.12), we have

$$(4.14) \quad n(\hat{\rho}(h) - \rho(h)) = n(\hat{\rho}(h) - \rho(h)) + \frac{n(\hat{\rho}(h) - 1)n\bar{X}^2}{\sum_{t=1}^n (X_t - \bar{X})^2} + \frac{n\bar{X}(\sum_{j=1}^h (X_j - X_{n+j}))}{\sum_{t=1}^n (X_t - \bar{X})^2}.$$

By Theorem 4.4 the first term is $O_p(a_n^{-1} a_n^{-2} n) = O_p(1)$ since $\alpha < 1$. The third term in (4.14) is also negligible because $n\bar{X} = O_p(a_n)$, $(\sum_{t=1}^n (X_t - \bar{X})^2)^{-1} =$

$O_p(a_n^{-2})$, and $\sum_{j=1}^h (X_j - X_{n+j}) = O_p(1)$ so that the product of the three terms is

$O_p(a_n^{-1}) = O_p(1)$. As for the middle term,

$$\frac{n(\hat{\rho}(h) - 1)n\bar{X}^2}{\sum_{t=1}^n (X_t - \bar{X})^2} \Rightarrow \frac{(\rho(h) - 1)(\sum_1^{\infty} c_i S)^2}{(\sum_1^{\infty} c_i^2) S_0}$$

follows from (4.13) and the weak consistency of $\hat{\rho}(h)$. Finally the joint convergence in the statement of the corollary is clear. \square

We close this section with a comparison of the standard result for the correlation function in the finite variance case and Theorem 4.4. Assuming that Z_t has a finite variance and a zero mean, Theorem 8.4.6 of Anderson (1971) gives

$$n^{1/2}(\hat{\rho}(1) - \rho(1), \hat{\rho}(2) - \rho(2), \dots, \hat{\rho}(l) - \rho(l)) \Rightarrow (V_1, V_2, \dots, V_l)$$

where the limit vector has a multivariate normal distribution with mean zero and covariance matrix given by Bartlett's formula

$$r_{gh} = \sum_{j=-\infty}^{\infty} (\rho(g+j)\rho(h+j) + \rho(g-j)\rho(h+j) - 2\rho(j)\rho(g)\rho(h+j) \\ - 2\rho(j)\rho(h)\rho(g+j) + 2\rho^2(j)\rho(g)\rho(h)).$$

However, by checking covariances the components in the limit vector may be written as

$$(4.15) \quad v_h = \sum_{j=1}^{\infty} (\rho(h+j) + \rho(h-j) - 2\rho(j)\rho(h)) S_j, \quad h = 1, 2, \dots, \ell$$

where $\{S_j\}$ is a sequence of iid $N(0, 1)$ random variables. This corresponds to the numerator portion of the limit in Theorem 4.4 with $\alpha = 2$. In fact, S_j may be identified as the weak limit of $\sigma^{-2} n^{-1/2} \sum_{t=1}^n Z_t Z_{t+j}$, $j = 1, 2, \dots$. Moreover, in the finite variance case, the sample variance $n^{-1} \sum_{t=1}^n X_t^2 \xrightarrow{P} \sum_{j=-\infty}^{\infty} c_j^2 \text{Var}(Z_1) > 0$ whereas $a_n^{-2} \sum_{t=1}^n X_t^2 \Rightarrow \sum_{j=-\infty}^{\infty} c_j^2 S_0$ in the $0 < \alpha < 2$ case. This phenomenon accounts for the division by S_0 in Theorem 4.4 and not in (4.15).

5. Examples

In this section, we consider applications of Theorem 4.4 to some time series models. Throughout this section, assume the hypotheses of Theorem 4.4 are met and, for simplicity, suppose the distribution of Z_t is symmetric. We then have

$$(5.1) \quad n^{1/\alpha} \tilde{L}(n) (\hat{\rho}(h) - \rho(h)) \Rightarrow \sum_{j=1}^{\infty} (\rho(h+j) + \rho(j-h) - 2\rho(j)\rho(h)) S_j / S_0$$

where $\tilde{L}(n)$ is a slowly varying function and S_1, S_2, \dots is now an iid sequence of symmetric α -stable random variables, independent of the positive $\alpha/2$ -stable random variable S_0 .

The numerator of the limit in (5.1) is also a symmetric α -stable random variable with characteristic function given by

$$(5.2) \quad \exp \left\{ - \sum_{j=1}^{\infty} |\rho(h+j) + \rho(j-h) - 2\rho(j)\rho(h)|^{\alpha} |t|^2 \right\}$$

Extending the notion of variance for a Gaussian random variable, Stuck (1978) defined the dispersion of a random variable with characteristic function (5.2) by

$$(5.3) \quad \text{disp} = \sum_{j=1}^{\infty} |\rho(h+j) + \rho(j-h) - 2\rho(j)\rho(h)|^{\alpha}$$

(see also Cline, 1983). The limit in (5.1) is then equal in distribution to $(\text{disp})^{1/\alpha} S_1/S_0$. Notice that upon setting $\alpha = 2$ in (5.3), we get the asymptotic variance of $\hat{\rho}(h)$ in the traditional finite second moment setting.

1) MA(q). Suppose $\{X_t\}$ is the finite moving average

$$X_t = Z_t + \theta_1 Z_{t-1} + \dots + \theta_q Z_{t-q}.$$

Then, since $\rho(h) = 0$ for $|h| > q$, we have for $h > q$

$$n^{1/\alpha} L(n)(\hat{\rho}(h) - \rho(h)) \Rightarrow (1 + 2 \sum_{j=1}^q |\rho(j)|^{\alpha})^{1/\alpha} S_1/S_0.$$

2) Estimation of θ in a MA(1). For the MA(1) process $X_t = Z_t + \theta Z_{t-1}$, $\rho(1) = \theta/(1 + \theta^2)$. A method of moments type estimator for θ is found by solving the latter equation for θ . Choosing the solution with the constraint $|\theta| \leq 1$ (cf. Fuller, 1976), gives

$$\hat{\theta} = \begin{cases} (1 - (1 - 4\hat{\rho}^2)^{1/2})/(2\hat{\rho}) & \text{if } 0 \leq |\hat{\rho}| \leq .5 \\ -1 & \hat{\rho} < -.5 \\ 1 & \hat{\rho} > .5 \end{cases}$$

where $\hat{\rho} = \hat{\rho}(1)$. Letting $g(\rho)$ denote the inverse of the function $\theta/(1 + \theta^2)$ with $|\theta| \leq 1$, we have by the mean value theorem

$$\hat{\theta} - \theta = g(\hat{\rho}) - g(\rho) = g'(\rho)(\hat{\rho} - \rho) + o_p(\hat{\rho} - \rho).$$

Hence

$$n^{1/\alpha} L(n)(\hat{\theta} - \theta) \Rightarrow (1 - \theta^2)^{-1} (1 + \theta^2)^2 ((1 - 2\rho^2(1))^{\alpha} + |\rho(1)|^{\alpha})^{1/\alpha} S_1/S_0.$$

The dispersion of the numerator of the limit simplifies to

$$\frac{(1 + \theta^4)^{\alpha} + |\theta|^{\alpha}(1 + \theta^2)^{\alpha}}{(1 - \theta^2)^{\alpha}}. \quad \text{Again note by setting } \alpha = 2, \text{ we obtain the asymptotic}$$

variance of $\hat{\theta}$ (cf. Fuller, 1976, p. 343).

3. AR(1). Let $\{X_t\}$ be the AR(1) process $X_t = \phi X_{t-1} + Z_t$ where $|\phi| < 1$. In this case, $\rho(h) = \phi^{|h|}$ and estimating ϕ by $\hat{\phi} = \hat{\rho}(1)$, we have

$$\begin{aligned} n^{1/\alpha} \tilde{L}(n)(\hat{\phi} - \phi) &\Rightarrow \left(\sum_{j=1}^{\infty} (\phi^{1+j} + \phi^{j-1} - 2\phi^j \phi^\alpha)^{1/\alpha} \right) S_1/S_0 \\ &= \frac{1 - \phi^2}{(1 - \phi^\alpha)^{1/\alpha}} S_1/S_0. \end{aligned}$$

4. Yule-Walker estimates. The Yule-Walker matrix equation for the AR(p)

model $X_t = \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + Z_t$, assuming $1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p \neq 0$ $|z| \leq 1$, is

$$(5.4) \quad R \phi = \rho$$

where R is the $p \times p$ matrix $[\rho(i-j)]_{i,j=1}^n$, $\phi = (\phi_1, \dots, \phi_p)'$

and $\rho = (\rho(1), \dots, \rho(p))'$. The Yule-Walker estimate of ϕ is then defined as the solution of (5.4) with R and ρ replaced by $\hat{R} = [\hat{\rho}(i-j)]_{i,j=1}^n$ and

$\hat{\rho} = (\hat{\rho}(1), \dots, \hat{\rho}(p))'$, respectively. As in Yohai and Maronna (1977), for $z \in \mathbb{R}^p$ define $\psi(z) = R(z)^{-1} z$ where $R(z) = [z_{i-j}]_{i,j=1}^n$ and $z_0 \equiv 1$. Since $\hat{R} \xrightarrow{P} R$ and R is non-singular, this implies $\psi(\hat{\rho})$ is well defined for large n .

The mean value theorem then gives

$$\hat{\phi} - \phi = D(\hat{\rho} - \rho) + o_p(\hat{\rho} - \rho)$$

where D is the $p \times p$ matrix of partial derivatives of ψ evaluated at ρ . Consequently,

$$n^{1/\alpha} \tilde{L}(n)(\hat{\phi} - \phi) \Rightarrow D \tilde{Y}$$

where $\tilde{Y} = (Y_1, Y_2, \dots, Y_p)'$ with $Y_h = \sum_{j=1}^{\infty} (\rho(h+j) + \rho(h-j) - 2\rho(j)\rho(h)) S_j/S_0$ $h = 1, \dots, p$.

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